Design of Comminution Circuits for Improved Productivity Using a Multi-Objective Evolutionary Algorithm (MOEA)

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The performance of a processing plant has a large impact on the profitability of a mining operation, yet plant design optimisation decisions are based on past experience and intuition rather than on scientific analysis. Genetic algorithms as a tool for circuit analysis in plant design and optimisation was considered. The multi-objective evolutionary algorithm initialises the plant design and optimisation based on experimental results, which are used to formulate and determine the objective function values. A simulation was conducted to assess the performance of candidate solutions. The two optima are then traded-off using cost objective, which is sought to be minimized. Once an optimum was selected, the circuit mass balance and equipment design was performed, bringing the theory of network design and genetic algorithms into unison. Results of the study provide financial benefits, optimal parameter settings for the comminution equipment and ultimately better plant performance.

Keywords - **Comminution circuits, evolutionary algorithms, multi-objective optimisation,**

I INTRODUCTION

It is expected that Zimbabwe will expand its platinum ore mining operations significantly in the next two years to take advantage of the current strength of the mineral on the global market. It is with this expected growth of the mines that a need for the optimisation of the mining operations (mining, crushing, screening, grinding, concentration, smelting and refining) is necessary to meet the anticipated increase in the demand and/or throughput. MMC is pseudo name for one platinum mining company in Zimbabwe. MMC operations were used as the base case for the design and optimisation of the comminution circuits. Although MMC is the base case the results obtained from this paper are intended to be applicable to any organization that has a Crushing, Screening and Grinding Sections in their operations. Iron-ore, coal ore and platinum ore are some of the major minerals extracted in Zimbabwe. Similar work has been applied to coal in [1].

The problem of MMC was how to improve the performance of crushing, screening and grinding in minerals processing operations thus increase throughput while maintaining operating costs minimum. One way to solve problem was through experimental methods through comparison of alternative handcrafted designs. This is a time consuming process and lack of analytical models. This means that there is little theoretical guidance to narrow the search for better solutions.

The aim of this paper is to develop optimum operational parameters for comminution circuit equipment through Multi-Objective Evolutionary Algorithms (MOEAs) for increased productivity at MMC. The objectives of the study were set as follows:

1. To model a competent, efficient and effective evolutionary algorithm for:
   i) Determination of the product screen aperture size
   ii) Determination of the crushing product size (D_{80})
2. Develop a visual basic simulator (Qwiksim©) programme to determine the parameters above
3. Compare cost of current scenario on the ground and the simulated results, that is, to evaluate the simulator effectiveness and for trading off results obtained in minimization and maximization objective functions.

The rest of the paper is organised as follows. Section II gives a brief background to comminution circuits, while Section III provides a background to multi-objective evolutionary algorithms. Problem formulation is outlined in Section IV, and a case study on MMC operations is provided in Section V. Section VI presents experimental optimisation results. Finally, Section VII provides conclusions and further research prospects.

II COMMINUTION CIRCUITS

Comminution is defined in [2] as collection of physical processes that can be applied to a stream. Reference [3] says comminution involves crushing, screening and grinding process to reduce the ore size for eventual metal liberation through the flotation process. A comminution circuit consists of a collection of processing units connected together by conveyor belts mostly. *Comminution circuits* contain loops which re-cycle large particles through crushers until they reach the desired size, [2]. *Productivity* in comminution is the ratio of the output per unit of input over time and it is a measure of efficiency, [4].

In this paper, we focus on the size reduction of the ore and we do not cover the mineral extraction processes such as flotation or cyanidation. The paper did not cover the volumetric capacities of the grinding mill. The grinding mill was assumed to be a black box operation. Comminution circuits have been operated based on engineering intuition and this can be a time consuming process. By optimising these parameters, the paper will not only attempt to solve the problems that are faced at MMC, but also situations that are problematic in comminution circuits worldwide.

III MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS

Evolutionary algorithms is an umbrella term used to describe computer based problem solving systems which use computational models of some of the known mechanisms of evolution as key elements in their design and implementation. Examples are Genetic Algorithms, Evolutionary Programming, Evolutionary Strategies, Classifier Systems, and Genetic Programming, [4]. Multi-Objective solutions consist of multiple decision objectives such as cost minimization and throughput maximization [2]. *Optimisation* entails maximizing or minimizing a parameter variable for example; cost, production time, labour and throughput, [5]. Similar work has done in [6], [7].

Optimisation algorithms can be classified into:
(i) Single-variable Optimisation Algorithms,
(ii) Multi-variable Optimisation Algorithms,
(iii) Constraint Optimisation Algorithms,
(iv) Specialized Optimisation Algorithms, and
(v) Non-Traditional Optimisation Algorithms [8].

Multi-Objective Evolutionary Algorithms (MOEA) generally comprises of seven steps shown in [7]:

Step 1: Randomly generate strings of length l_i in a population of size n. The following parameters are crucial:

- $t_{\max}$ maximum number of generations,
- p_c probability of crossover,
- p_m mutation operator specifying the probability of mutation.

Step 2: Evaluate the population strings generated in Step 1.

Step 3*:* Initialise t the generation counter at $t = 0$.

Step 4: Perform the selection using anyone of the selection methods such as roulette-wheel selection, stochastic universal sampling, local selection, truncation selection or tournament selection as discussed in [4].

Step 5: Perform chromosome crossover on the random pairs of strings. The crossover is based on the crossover probability and a random selection of crossover site [6], [8].

Step 6: Perform mutation on the chromosomes random position in the strings based on the probability of mutation.

Step 7: Evaluation of strings in the new population. Setting t = t + 1**.** If $t > t_{max}$, terminate, or else go to Step 3.

IV PROBLEM FORMULATION

Due to strengthening of platinum price MMC aimed at increasing the amount of platinum recovered from the ore through efficiently designing variables for the equipment used in the process. The following steps for optimal design were applied: identifying need for optimisation, choice of design variables, formulation of constraints, formulation of objective function, choice of optimisation methods and problem solution as guided in [4].

After completing the computation run, a trade-off between the two set optima was performed. A third objective was set to select between the two optima. Each component in the comminution circuit could be replaced with a number of physical machines operating in parallel and the cost of each component depends on the number of physical machines used. Component cost is however non-linear with respect to the number of physical machines due to the more complex layout and the extra conveyors needed. For a component c with a unit count of n_c, the cost of the component has been modelled in [2]:

$$cc_c = n_c(mc_c)(0.9 + 0.1n_c) \tag{1}$$

Where:
cc_c is the component cost
mc_c is the machine cost
The total cost of the circuit is the sum of all the components making up the circuit shown in equation (2). The third objective was evaluating the performance of a comminution circuit is the minimization of the total cost.

$$Total\_Circuit\_Cost = \sum_{c=1}^{M} cc_c \tag{2}$$

where, M is the maximum number of components.

A. Grinding Circuit Optimisation

In essence the grinding circuit was optimised in terms of the throughput that would be expected from the crushing and screening section based on a 5% re-conciliatory margin. The grinding circuit includes the mill discharge pumps, which have to be optimised as well to meet the increased throughput and maintain a performance level of 70% sump level.

B. Grinding Media Optimization

Since the process of optimisation sought to obtain a trade-off between a maximized capacity and a minimized D_{80} size, the ball size had to be changed in accordance with the minimization objective. Ball size is one of the principal factors affecting the efficiency and capacity of the ball mills. The general principle of selection is that the proper size of the makeup balls is the size, which will just break-up the largest feed particles. If the balls are too large, the number of breaking contacts is reduced, thereby reducing efficiency of grinding. If the balls are too small there will be wasted contacts of force insufficient to break the particles, hence grinding efficiency is also reduced. The proper makeup ball size, B, is [9]:

$$B = \left(\frac{F}{K}\right)^{\frac{1}{2}} \times \left(\frac{(S_g \times W_i)}{(100 \times C_s \times \sqrt{D})}\right)^{\frac{1}{3}} \qquad (3)$$

Where, F represents the feed size in microns 80% of the feed passes, W_i is the work index of platinum ore, C_s is fraction of mill critical speed, S_g: denotes the specific gravity of material, D is the mill diameter in feet, and K is the empirical experience constant usually 350 for wet grinding. N_c the critical speed of the Mill is calculated in [3] as:

$$N_C = \frac{42.29}{\sqrt{D}} \qquad (4)$$

C_s the fraction of Mill Critical Speed is the computed in [3] as follows:

$$C_S = 0.013505 \times N_C \times \sqrt{D} \qquad (5)$$

V MMC OPERATIONS STUDIED

The permissible reduction ratio of the crushing and Screening Plant at MMC is 1:4, [10]. DRA a process engineering company deduced the ratio through practical extensive test of the MMC ore. The primary jaw crusher, a Nordberg C110 is employed for the initial size reduction of ore. The current operation sees the crusher being utilized with the machine parameters as shown in Table I.

TABLE I
CRUSHER FEED STREAM

Solids (tons/hour)	400
D_{50} Size (tons/hour)	100
D_{80} Size (tons/hour)	250
Max. Size (mm)	400

The primary crusher discharge conveyor has the capability of handling the following stream of ore and operates with the parameters as shown in Table II.

TABLE II
CRUSHER DISCHARGE STREAM AND DISCHARGE CONVEYOR PARAMETERS

Solids (tons/hour)	400
D_{50} Size (mm)	40
D_{80} Size (mm)	90
Max. Size (mm)	400
Trough Angle (Deg)	35
Belt Width/Fabric Plies	900/3
Speed (m/s)	0.98

The jaw crusher and the jaw crusher discharge conveyor stand out as areas for potential improvement to optimise throughput.

VI MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM PROGRAMMING FLOW STRUCTURE

For the program to perform the evolutionary computation of a 2-dimensional array size 60 rows by 1920 columns, an in depth analysis of the Algorithm procedure was required. The Algorithm procedure involved calling of two procedures, which will output part computation of the algorithm.

A Procedure 1

This stage initialises the computational array of the evolutionary algorithm. Random numbers were generated for the subsequent computation of the variables and the objective function. After completion of Procedure 1 the program was designed to loop and increment variable j representing the computational array columns. The steps in this procedure initialised the parent population for the genetic/ evolutionary run. The parent population was thus generated using Microsoft's Visual Basic 6.0 random number Generation function (Rnd), [11]. Procedure 1 is summarised in Figure 1.

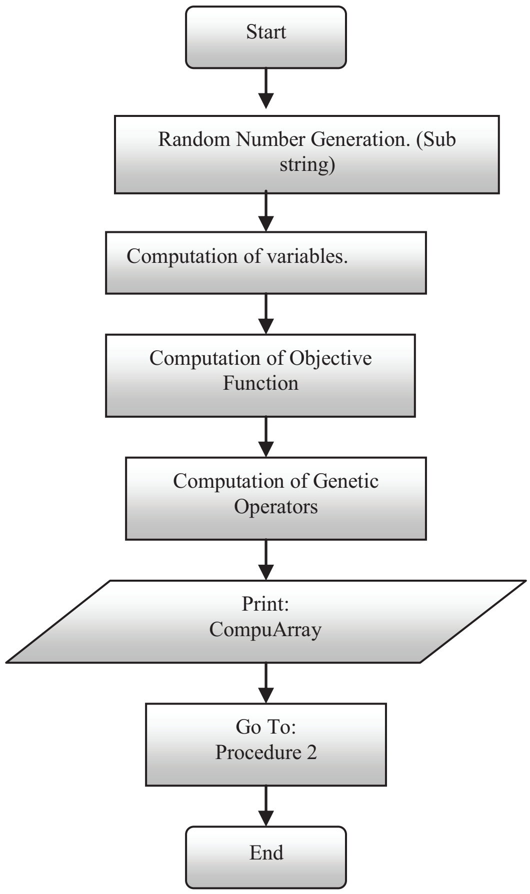

Fig. 1. Procedure 1 flowchart.

The sub-strings were converted to variable quantities using the conversion function from [2] shown in equations (6) to (8):

$$x_i = \zeta \times \beta \quad (6)$$

Where:

$$\zeta = \sum 2^p \times \{1,0\} \quad \text{a constant} \quad (7)$$

$$\beta = x_i^L + \left[\frac{\left(x_i^U - x_i^L\right)}{\left(2^l - 1\right)} \right] \quad (8)$$

x_i is variable to be optimised
p is the probability of permutation
x_i^L is the Lowerbound of the variable x_i
x_i^U is the Upperbound of the variable x_i
β is the decimal form of the decoding parameter string
l is the length of the string

The computation was done until the entire population was generated and the variable value obtained.

The computation of the objective function was based on expression (9):

$$y_1 = 4.68x_1 + 0.44x_2 - 0.02x_3 + 1.33x_4 \quad (9)$$

Where:
y_1 is the comminution circuit capacity (tons per hour)
x_1 is the circuit feed (tons per hour)
x_2 is the secondary crusher closed side settings (mm)
x_3 is the Rpm of the crusher head (revolutions per minute)
x_4 is the screen aperture size (mm)

The value of the objective function is stored in the CompuArray for comparison of optimal values once the generation is complete. The selection operator is probabilistic and depends on the expected count (A) and the cumulative probability (B). The crossover and the mutation operator are also stochastic parameters with probabilities of 0.8 and 0.05 respectively for the particular Genetic Algorithm (GA) run, [4]. The second procedure is called after the first generation of the GA run has been created.

B. Procedure 2

Procedure 2 differs from Procedure 1 in that it is initialised by the intermediate population from Procedure 1 rather than by random number generation. The intermediate population is the child population and initialises the next generation operations. The rest of the computation is similar to that of Procedure 1.

VII OPTIMISATION RESULTS

A Genetic Algorithms Results and Cost Objective

The results are based on 60 generations (t_{max}=60), population size (μ) of 20 and a child population (λ) of 20. The optima satisfying the maximization and minimization objectives are displayed in Table III.

TABLE III
RESULTS OF THE MOEA RUN BASED ON A SEARCH WITH 60 GENERATIONS

Parameter	**MMC Best Capacity Value**	**MOEA Best D_{80} Value**
Capacity (tons/hour)	516.4	327
Closed Side Setting (mm)	19.68	18.25
Circuit Feed (tons/hour)	1000	587.30
Countershaft Speed (RPM)	780.9	819.05
Screen Aperture Size (mm)	16.57	14.98
D_{80} Particle Size (mm)	11.10	10.03

Evaluation time on a Pentium 3 processor, at 700 MHz took 75.30 seconds. Sixty (60) generations were used to give the quickest convergence to the global search and this was considered adequate for the operational application of the simulation package (non-commercial). The cost objective was determined from the mass balance.

B Cost Objective Evaluation

The cost objective also referred to as the "$" objective in this paper is used to provide an option of selection of the optima to use based on the best-cost savings. The results for the total cost based on the best capacity objective are shown in Table IV.

TABLE IV
COMPUTATION OF THE TOTAL CIRCUIT COST BASED ON THE BEST CAPACITY OBJECTIVE

Component *c*	**Machine Count(n_c)**	**Machine Cost per Unit (US$)**	**Component $Cost_c$(US$)**
Sec. Crusher	4	110,000.00*	572,000.00
Product Screen	4	36,000.00*	187,200.00
Tertiary Crusher	1	110,000.00*	110,000.00
Scalping Screen	4	26,000.00*	135,200.00
Total Circuit Cost (US$)			**1,004,400.00**

* Factory Cost excluding Transporting and other costs involved

C Total Circuits Cost Evaluation Based On Best D_{80}

Using the least cost objectives, the optima (maximization and minimization) to select from the two global optima, the Best D_{80} optimal solution was at a total circuit cost of US$ 729,000.00 compared to the cost that will be incurred if the circuit were to be designed and installed based on the MMC Best Capacity solution with a total cost of US$1,004,400.00. The results for the Best D_{80} optimal solution are shown in Table V.

TABLE V
COMPUTATION OF THE TOTAL CIRCUIT COST BASED ON THE MOEA BEST D_{80} OBJECTIVE

Component *c*	**Machine Count (n_c)**	**Machine Cost per Unit (US$)**	**Component $Cost_c$ (US$)**
Sec. Crusher	3	110,000.00*	396,000.00
Product Screen	3	36,000.00*	129,600.00
Tertiary Crusher	1	110,000.00*	110,000.00
Scalping Screen	3	26,000.00*	93,600.00
Total Circuit Cost (US$)			**729,200.00**

*Factory Cost excluding transport cost and other costs such as taxes and duty for importation involved

For the trade-off decision the third objective of cost minimization was used. One of the two optima was chosen based on the cost trade-off. The analysis of the proposed circuit was compared with the analysis of the current circuit in operation and the merit of the proposed circuit over the current operational circuit was detailed. The comminution circuit was analysed from the open circuit secondary crusher to the tertiary crusher and then the grinding circuit.

VIII CONCLUSIONS

Optimum operating parameters for improved productivity in comminution circuit with MMC as the case study were developed. The aim was achieved through the global search technique of evolutionary algorithms. Optimal results were achieved and recommended for use in the expansion programme at MMC. After mathematically modelling the circuit performance, software was designed coded QwikSim® for the determination and selection of the following, [12]:

1. Vee-belt drive transmission requirement
2. Conveyor belt requirement for bulk material transfer
3. The mill discharge pumping requirements
4. The crusher operational settings i.e. closed side setting, head rotational speed and feed into the crusher
5. The product screen aperture requirement
6. The machine count
7. Mass balancing the circuits

The study has provided an optimisation technique for the entire design for the processing plant. It co-evolved the numerical control settings for the processing equipment as well as design of the circuit itself. Further work that can be considered is in network design, which is another area where evolutionary algorithms have been successfully applied.

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